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## ***Scaleable Object Recognition with a Belief Model***

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### ***Cross-Reference to Related Application***

This patent application is a Non-Provisional Patent Application of related Provisional Patent Application Serial Number 60/212,050, ~~(Attorney Docket 37005-163533)~~ "Scaleable Object Recognition Using a Belief Model," to Bella, et al., filed June 16, 2000, the contents of which are incorporated herein by reference in their entirety. M.P. 6/4/05

### ***Background of the Invention***

#### ***Field of the Invention***

The present invention relates generally to expert systems and more particularly to recognition systems.

#### ***Related Art***

Conventional image recognition systems are not well suited to recognizing arbitrary objects. The sheer number of possible objects to be recognized, and the infinite variety of representations, relations, views and scale give rise to a multitude of intricate problems. In addition, the sources of raw image data are quite large. For example, images that may need to be analyzed by a company or government agency can be captured from various content sources including, e.g., the worldwide web (WWW), newspapers, magazines, flyers, cameras, airplanes, missiles, people, signs, buildings, maps and various video sources such as, e.g.,

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newscasts, documentaries, camcorders, teleconferences, digital and analog video, people, and locations. A scaleable approach in terms of database size and the number of recognizable objects is needed to adequately filter and route this data.

Conventional object recognition solutions have shortcomings. The conventional  
5 solutions are geared towards recognizing specific objects of interest. The conventional solutions do not handle arbitrary images and do not easily scale to larger domains in terms of the numbers of objects they recognize.

What is needed then is a solution that provides adequate scaleability in terms of speed, accuracy, and domain size.

#### *Summary of the Invention*

An exemplary embodiment of the present invention is directed to a system, method and computer program product for providing an object recognition blackboard system architecture.

In an exemplary embodiment of the present invention, the system for recognizing  
10 objects in content can include ~~a~~ blackboard comprising a plurality of experts, and data comprising original input data and data created by processing of any of the plurality of  
15 experts, and a controller operative to control the experts ~~a~~ belief model, coupled to the controller, comprising a set of beliefs and probabilities associated with each belief of the set  
20 of beliefs ~~a~~ belief network, coupled to the controller ~~a~~ and a relations subsystem, coupled to the controller.

In an exemplary embodiment, the experts can include expert object recognizers  
25 including experts such as, e.g., region identification experts; color region experts; a corner

recognizer; a closed curve recognizer; a roof recognizer; a text recognizer; simulated experts; microphone recognizer; space suit recognizer; satellite recognizer; a geometric shape recognizer; a building recognizer; an egg recognizer; a dice recognizer; a person recognizer; a face recognizer; or a product recognizer.

5 In an exemplary embodiment, the data can include, ~~e.g.~~, relations data; expert status data; image subsection data; and the belief model.

In an exemplary embodiment, the controller can be configured to be operative to choose chosen experts from the plurality of experts which are to be executed; ~~to be operative~~ to schedule execution of the chosen experts; ~~or to be operative to execute the chosen experts.~~

10 In an exemplary embodiment, the blackboard can further include storage for receiving an input image; ~~or a reporter operative to output results of processing.~~

In an exemplary embodiment, the belief model can include a set of rules deduced from a learning system which describes how different classes recognized by the system are related to each other spatially and physically.

15 In an exemplary embodiment, the belief model is operative to predict existence of a shadow object in an image even if there are no specific experts capable of recognizing the shadow object.

20 In an exemplary embodiment, the belief network is operative to combine beliefs in output data output by the experts and probabilities drawn from the belief model into a single belief for a given object.

In an exemplary embodiment, the relations subsystem is operative to determine how returned objects returned by the experts are related to each other.

In an exemplary embodiment, the relations subsystem is operative to determine spatial relations.

In an exemplary embodiment, the spatial relations include types including, e.g., a north type, a south type, an east type, a west type, a contains type, a contained by type, or an adjacent to type.

In an exemplary embodiment, the relations subsystem is operative to determine temporal relations.

In an exemplary embodiment, the temporal relations include types including: a before type, an after type, or an exists with type.

In an exemplary embodiment, the content can include: video; an image; digitized content; or a frame.

In an exemplary embodiment, the belief model is generated by a learning system.

In an exemplary embodiment, the learning system includes: truth data files for deducing beliefs, probabilities and shadow objects; a learning system controller; or a statistics space controlled by the controller.

In an exemplary embodiment, the learning system is operative to assist in integrating a new expert wherein the new expert has been created, encapsulated, compiled, a stub function has been added to the blackboard, if output is new has been added to the belief model, and a blackboard rule has been added to control when the new expert will be executed.

In an exemplary embodiment, the belief network is a/a Bayesian Network, a mean probability, or a Dempster-Shafer Network. *M.B. 6/4/95*

In an exemplary embodiment, the belief model includes rules operative to be used to make a determination whether or not one of the experts should be executed by search of the belief model to determine whether an adaptable threshold of supporting evidence has been exceeded for an execution supportability rule that evaluates outputs of currently executing experts.

In an exemplary embodiment, the belief model is operative to model expected object associations, to weigh relative object positions, and to tie a probability or belief value to those associations.

In an exemplary embodiment, the belief network is operative to combine the belief model with hypotheses generated by the experts to form belief values for hypothesized objects.

In another exemplary embodiment of the present invention a method of recognizing objects is disclosed including identifying classes of objects specified by a user using a plurality of cooperative object recognition experts, achieving higher accuracy from using in parallel the plurality of cooperative object recognition experts than is achievable using in serial the plurality of cooperative object recognition experts, supporting scalability of performance including supporting multiple processors, developing a belief model including specifying specified associations among the objects, learning learned associations among the objects, representing the specified and learned associations, and forming a belief network wherein the belief network is at least one of a Bayesian Network and a Dempster Shafer Network, and deducing shadow objects from the belief model.

In another exemplary embodiment, a method for adding a new expert to a blackboard is disclosed including creating an expert, encapsulating the expert, compiling the expert,

adding a stub function to a blackboard/~~determining~~ if output of the expert is new and if new, *M.B. 6/4/05*  
then adding the output's class to the blackboard, and updating a belief model by providing  
truth data file data to a learning system/~~and~~ creating a rule to control when the new expert is *M.B. 6/4/05*  
to be executed when supporting evidence is found to exceed an adaptable threshold.

5 In an exemplary embodiment, the system can include a plurality of experts/~~a~~ belief *M.B. 6/4/05*  
model/~~and~~ a controller operative to control processing of the plurality of expert object *M.B. 6/4/05*  
recognizers on image.

The belief model, in an exemplary embodiment, can model expected object  
associations, such as, ~~e.g.~~, relative object positions, and can tie a probability or belief value to *M.B. 6/4/05*  
those associations.

The blackboard controller in an exemplary embodiment can further include a belief  
network operative to combine the belief model with hypotheses generated by plurality of  
expert the object recognizers to form belief values for hypothesized objects.

The present invention, in an exemplary embodiment, can provide for easy  
modification of the belief model, and due to extensibility of the object recognition  
Blackboard system architecture, can be easily scaled to incorporate additional objects and  
new technologies.

The present invention can provide various advantages. The present invention  
advantageously recognizes that using a combination of the plurality of expert object  
20 recognizers more accurately recognizes certain types of objects.

Further examples of advantages include, ~~e.g.~~, object recognition accuracy can be *M.B. 6/4/05*  
gained over conventional expert object recognizers executed alone/~~performance~~ can be *M.B. 6/4/05*  
gained using parallel processing over the conventional expert object recognizers executed

serially/relative ease of extending domain size by integration of new technologies and M.B. 6/4/85  
objects by a user/and the ability to define and predict scene information and existence of M.B. 6/4/85  
objects for which specialized expert object recognizer processing does not exist.

Further features and advantages of the invention, as well as the structure and operation  
5 of various embodiments of the invention, are described in detail below with reference to the  
accompanying drawings.

### *Brief Description of the Drawings*

The foregoing and other features and advantages of the invention will be apparent  
10 from the following, more particular description of a preferred embodiment of the invention,  
as illustrated in the accompanying drawings wherein like reference numbers generally  
indicate identical, functionally similar, and/or structurally similar elements. The left most  
digits in the corresponding reference number indicate the drawing in which an element first  
appears.

15 FIG. 1A depicts an exemplary embodiment of a block diagram of an image object  
recognition blackboard system according to the present invention illustrating data  
instantiation and data flow;

FIG. 1B depicts an exemplary embodiment of a block diagram of an image object  
recognition blackboard system according to the present invention illustrating data flow and  
20 control flow;

FIG. 2 depicts an exemplary embodiment of a block diagram of exemplary city, nest  
and dice scenes illustrative of examples of the present invention;

FIG. 3 depicts an exemplary embodiment of a block diagram of a learning system of

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the image object recognition blackboard system according to the present invention;

FIG. 4 depicts an exemplary embodiment of a block diagram of an exemplary four quadrant cartesian coordinate plane illustrating quadrant overlap for use in performing image object recognition according to the present invention;

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5 FIGs. 5A-5D depict an example of the output of each of the region identification experts described according to an exemplary implementation of the present invention;

FIG. 6 depicts a chart graphing belief versus images for scene prediction for generic news images according to an exemplary embodiment of the present invention;

FIG. 7 depicts a chart graphing belief versus images for scene prediction for space  
10 images according to an exemplary embodiment of the present invention;

FIG. 8 depicts a chart graphing belief versus image for scene prediction for soccer images according to an exemplary embodiment of the present invention;

FIG. 9 depicts a chart graphing number of shadow objects versus images for number  
of predicted shadow objects compared to number of true shadow objects according to an  
15 exemplary embodiment of the present invention;

FIG. 10 depicts a chart graphing average belief versus image for true shadow object predictions against false shadow object predictions according to an exemplary embodiment of the present invention; and

FIG. 11 depicts a chart graphing average belief versus image for true shadow object  
20 predictions against false shadow object predictions minus scene shadow objects according to an exemplary embodiment of the present invention.



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achieved is encouraging.

It has been shown that the Blackboard framework of the present invention is capable of accepting actual image processing processes as experts, and of utilizing the output of those experts. It was possible to create a belief model that was capable of predicting correct scene classifications in our test data with a  $> 0.67$  percent accuracy. The belief model was also capable of predicting the possible existence of 6 non-scene shadow objects, although the final belief values of these object rendered the discrimination between true and false predictions to be somewhat ambiguous.

The results show that even with a less than perfect set of image processing experts and an overly simplified belief network, it was possible to combine the output from the experts and get useful results. If a more sophisticated belief network was implemented and a more specialized set of image processing experts and relation functions used, we believe that the ambiguity in non-scene shadow object prediction could be reduced while at the same time improving the scene prediction results.

#### Generic News Scenes

A total of 33 images of generic news footage were selected and processed. Table A1 shows the overall results for each of the images.

Table A1<sup>3</sup> M.B. 6/4/05

	Number of Real Objects In Image	Number Found	Average Belief	False Hits	Average Belief	Missed Object s	Number Of Shadow Objects In Image	Number Predicted	Average Belief	False Hits	Average Belief	Scene Prediction n (C/I)	Belief
Image 1	89	89	0.8355	0	0.0000	0	3	3	0.3352	3	0.3901	C	0.4667
Image 2	76	75	0.8049	1	0.2353	1	3	3	0.3173	3	0.3901	C	0.4667
Image 3	100	100	0.8026	1	0.2353	0	3	3	0.3168	3	0.3620	C	0.4667
Image 4	79	78	0.8107	1	0.2353	1	3	3	0.3327	3	0.3801	C	0.4667
Image 5	122	121	0.7514	2	0.4527	1	1	0	0.0000	6	0.4382	I	0.6207
Image 6	139	138	0.7487	2	0.4527	1	1	0	0.0000	6	0.4382	I	0.6207
Image 7	145	145	0.7038	0	0.0000	0	3	3	0.4548	4	0.3534	C	0.5832

Image 8	139	139	0.8135	0	0.0000	0	3	3	0.5379	3	0.4332	C	0.7451
Image 9	135	135	0.8116	0	0.0000	0	3	3	0.5499	3	0.4332	C	0.7451
Image 10	143	143	0.8062	0	0.0000	0	3	3	0.5388	3	0.4332	C	0.7451
Image 11	146	146	0.7824	0	0.0000	0	3	3	0.5150	3	0.4332	C	0.7451
Image 12	157	155	0.6007	1	0.2353	2	3	3	0.3052	4	0.3332	C	0.3893
Image 13	133	131	0.5121	1	0.2353	2	3	3	0.2651	4	0.3181	C	0.3369
Image 14	125	123	0.5379	1	0.2353	2	3	3	0.2786	4	0.3258	C	0.3395
Image 15	153	151	0.5153	1	0.2353	2	3	3	0.2487	4	0.3146	C	0.3108
Image 16	118	116	0.5716	1	0.2353	2	3	3	0.2799	4	0.3263	C	0.3404
Image 17	95	93	0.5591	1	0.2353	2	3	3	0.2805	4	0.3192	C	0.3686
Image 18	119	119	0.8404	2	0.2353	0	3	3	0.4342	3	0.3617	C	0.7326
Image 19	148	148	0.8210	1	0.2353	0	3	3	0.4379	3	0.3795	C	0.7326
Image 20	138	138	0.8470	1	0.2353	0	3	3	0.4637	3	0.3795	C	0.7326
Image 21	137	137	0.8506	1	0.2353	0	3	3	0.4612	3	0.3795	C	0.7326
Image 22	153	153	0.8367	1	0.2353	0	3	3	0.4395	3	0.3795	C	0.7326
Image 23	81	80	0.8090	0	0.0000	1	3	3	0.4035	3	0.4543	I	0.5096
Image 24	67	66	0.6754	1	0.2353	1	4	3	0.3346	3	0.3901	C	0.4667
Image 25	59	58	0.5860	1	0.2353	1	4	4	0.2745	3	0.3768	C	0.3860
Image 26	65	65	0.8097	0	0.0000	0	4	3	0.3975	3	0.4543	I	0.5096
Image 27	56	56	0.7569	0	0.0000	0	4	3	0.4215	3	0.4543	I	0.5096
Image 28	56	56	0.8149	0	0.0000	0	4	3	0.4277	3	0.4543	I	0.5096
Image 29	61	61	0.7909	0	0.0000	0	4	3	0.4187	3	0.4344	C	0.4667
Image 30	60	60	0.8147	0	0.0000	0	4	1	0.4092	3	0.4344	I	0.4499
Image 31	31	29	0.8901	1	0.2353	2	3	2	0.3786	4	0.4168	C	0.4667
Image 32	21	19	0.7829	1	0.2353	2	3	2	0.3786	4	0.4127	C	0.4667
Image 33	19	17	0.7179	1	0.2353	2	3	2	0.3786	4	0.4052	C	0.4667

### Space Scenes

A total of 37 images of space related footage were selected and processed. Table A2 4 M.B. 6/4/95 shows the overall results for each of the images.

Table A2 4 M.B. 6/4/95

	Number of Real Objects In Image	Number Found	Average Belief	FALS E Hits	Average Belief	Missed Object s	Number of Shadow Objects In Image	Number Predict ed	Average Belief	FALS E Hits	Average Belief	Scene Predictio n (C/I)	Belief
Image 1	13	13	0.6961	1	0.67	0	1	1	0.7138	5	0.4449	C	0.7138
Image 2	24	24	0.8514	1	0.67	0	1	1	0.7138	5	0.4449	C	0.7138
Image 3	10	10	0.7784	1	0.67	0	1	1	0.7138	5	0.4449	C	0.7138
Image 4	21	21	0.8547	1	0.67	0	1	1	0.7138	5	0.4449	C	0.7138
Image 5	52	52	0.7108	0	0	0	2	2	0.6168	0	0.0000	C	0.7457
Image 6	12	12	0.4824	0	0	0	2	2	0.6168	0	0.0000	C	0.7457
Image 7	37	37	0.8349	0	0	0	2	2	0.6168	0	0.0000	C	0.7457
Image 8	10	10	0.5107	0	0	0	2	2	0.6168	0	0.0000	C	0.7457
Image 9	119	118	0.7596	2	0.2353	1	2	2	0.4895	4	0.3103	C	0.7703
Image 10	114	113	0.7434	2	0.2353	1	2	2	0.4972	4	0.3322	C	0.7703
Image 11	121	120	0.7153	2	0.2353	1	2	2	0.5127	4	0.3833	C	0.7703
Image 12	126	125	0.7579	2	0.2353	1	2	2	0.5010	4	0.3329	C	0.7703
Image 13	128	127	0.7292	3	0.2353	1	2	2	0.4739	4	0.2748	C	0.7703

Image 14	136	132	0.7900	5	0.2353	4	3	3	0.4701	3	0.3438	C	0.7538
Image 15	136	132	0.6942	6	0.2353	4	3	3	0.4669	5	0.3711	C	0.7538
Image 16	128	124	0.7499	4	0.2353	4	3	3	0.4729	5	0.3748	C	0.7538
Image 17	115	111	0.5655	4	0.2353	4	3	3	0.4688	6	0.3137	C	0.7538
Image 18	131	127	0.7184	5	0.2353	4	3	3	0.4701	3	0.3438	C	0.7538
Image 19	92	90	0.8593	2	0.2353	2	2	2	0.5274	4	0.3904	C	0.8005
Image 20	103	101	0.8666	1	0.2353	2	2	2	0.5529	4	0.4038	C	0.8005
Image 21	114	112	0.8472	1	0.2353	2	2	2	0.5596	4	0.4038	C	0.8005
Image 22	121	119	0.8261	1	0.2353	2	2	2	0.5175	4	0.3334	C	0.8005
Image 23	113	111	0.8271	1	0.2353	2	2	2	0.5335	4	0.3545	C	0.8005
Image 24	110	108	0.7614	2	0.2353	2	3	3	0.4976	3	0.3617	C	0.7829
Image 25	110	108	0.7932	2	0.2353	2	3	3	0.4976	3	0.3617	C	0.7829
Image 26	104	102	0.8016	2	0.2353	2	3	3	0.4976	3	0.3617	C	0.7829
Image 27	84	83	0.7286	0	0	1	2	2	0.6037	0	0.0000	C	0.7307
Image 28	78	77	0.7301	0	0	1	2	2	0.6037	0	0.0000	C	0.7307
Image 29	72	71	0.7949	0	0	1	2	2	0.6037	0	0.0000	C	0.7307
Image 30	37	37	0.7603	0	0	0	3	3	0.5672	3	0.4332	C	0.7703
Image 31	38	38	0.7162	0	0	0	3	3	0.5672	3	0.4332	C	0.7703
Image 32	14	14	0.6109	0	0	0	3	3	0.5672	3	0.4332	C	0.7703
Image 33	36	34	0.7202	0	0	2	3	3	0.5767	3	0.4332	C	0.7829
Image 34	40	39	0.7296	1	0.2353	1	2	2	0.5384	4	0.3967	C	0.7703
Image 35	40	39	0.7296	1	0.2353	1	2	2	0.5384	4	0.3967	C	0.7703
Image 36	40	39	0.7296	1	0.2353	1	2	2	0.5384	4	0.3967	C	0.7703
Image 37	18	17	0.5235	1	0.2353	1	2	2	0.5212	4	0.3474	C	0.7703

### World Cup Soccer Scenes

A total of 37 images of World Cup soccer footage were selected and processed. Table

A.3 shows the overall results for each of the images.

Table A.3

	Number of Real Objects In Image	Number Found	Average Belief	FALS E Hits	Average Belief	Missed Object s	Number of Shadow Objects In Image	Number Predicted	Average Belief	FALS E Hits	Average Belief	Scene Prediction n (C/I)	Belief
Image 1	114	111	0.5798	6	0.2353	3	2	2	0.1733	5	0.3288	I	0.3838
Image 2	132	130	0.6413	4	0.2353	2	2	2	0.1758	5	0.3288	I	0.3850
Image 3	93	91	0.6349	3	0.2353	2	3	3	0.2036	4	0.3544	I	0.3828
Image 4	92	89	0.6427	3	0.2353	3	3	3	0.2061	4	0.3069	I	0.3849
Image 5	36	35	0.5295	2	0.2353	1	4	4	0.3299	2	0.4123	I	0.4667
Image 6	42	41	0.4482	3	0.2353	1	4	4	0.3228	2	0.3846	I	0.4667
Image 7	45	44	0.4384	4	0.2353	1	4	4	0.3147	2	0.3776	I	0.4667
Image 8	32	31	0.5475	5	0.2353	1	4	4	0.3093	2	0.3878	I	0.4667
Image 9	45	44	0.6134	2	0.2353	1	4	4	0.3376	2	0.3937	I	0.4667
Image 10	31	27	0.6297	2	0.2353	4	3	3	0.2455	3	0.3490	I	0.4667
Image 11	35	31	0.7761	2	0.2353	4	3	3	0.2566	3	0.3904	I	0.4667
Image 12	19	15	0.5119	2	0.2353	4	3	3	0.2511	3	0.3522	I	0.4667
Image 13	47	43	0.7012	3	0.3802	4	3	3	0.2595	3	0.4092	I	0.6326
Image 14	26	24	0.5351	0	0.0000	2	4	4	0.3732	0	0.0000	C	0.4499

Image 15	48	46	0.8248	0	0.0000	2	4	4	0.4277	0	0.0000	C	0.4499
Image 16	29	27	0.6403	0	0.0000	2	4	0	0.0000	0	0.0000	I	0.0000
Image 17	48	45	0.6621	2	0.4527	3	4	4	0.2481	2	0.6029	I	0.6326
Image 18	30	27	0.3800	3	0.5551	3	4	4	0.2586	2	0.5494	I	0.6671
Image 19	49	47	0.5561	3	0.5551	2	4	4	0.2341	4	0.4896	I	0.6671
Image 20	26	22	0.3653	1	0.2353	4	4	4	0.2634	0	0.0000	C	0.2803
Image 21	46	41	0.6731	1	0.2353	5	4	4	0.2660	0	0.0000	C	0.2803
Image 22	35	33	0.7476	2	0.4527	2	4	4	0.3611	2	0.6029	I	0.6326
Image 23	9	7	0.5132	0	0.0000	2	4	0	0.0000	0	0.0000	I	0.0000
Image 24	40	37	0.6253	2	0.2353	3	4	4	0.3376	2	0.4290	I	0.4667
Image 25	38	36	0.6080	0	0.0000	2	3	0	0.0000	0	0.0000	I	0.0000
Image 26	45	43	0.7476	1	0.2353	2	3	3	0.3408	1	0.3984	C	0.2872
Image 27	43	40	0.7715	2	0.4527	3	4	4	0.3124	2	0.6029	I	0.6326
Image 28	23	20	0.5556	2	0.4527	3	4	4	0.3014	2	0.6029	I	0.6326
Image 29	34	32	0.5205	3	0.3802	2	4	4	0.2677	2	0.6029	I	0.6326
Image 30	36	35	0.8859	0	0.0000	1	4	4	0.3501	0	0.0000	C	0.4361
Image 31	40	39	0.7694	0	0.0000	1	4	4	0.3097	0	0.0000	C	0.4361
Image 32	17	16	0.6878	0	0.0000	1	4	4	0.3182	0	0.0000	C	0.4361
Image 33	29	28	0.5863	0	0.0000	1	4	4	0.3003	0	0.0000	C	0.4361
Image 34	99	98	0.7733	2	0.2353	1	4	4	0.2771	2	0.3716	I	0.4667
Image 35	87	86	0.8114	3	0.2353	1	4	4	0.2754	2	0.3862	I	0.4667
Image 36	71	70	0.6381	2	0.2353	1	4	4	0.2880	3	0.3328	I	0.3917
Image 37	77	76	0.7082	4	0.4090	1	4	4	0.2682	4	0.5120	I	0.7507

# Belief Model: Definitions

U.S. 6/4/85 <sup>6</sup> Table B.1 lists the Ids associated with the identifiable object classes.

Table B.1 <sup>6</sup>

U.S. 6/4/85

Object Class	Id
Person	1
Face	2
Text	3
Microphone	4
Inset	5
Earth	6
Satellite	7
Space Suit	8
Soccer Field	9
Ball	10
Generic News Scene	11
Space Scene	12
Soccer Scene	13
Region type 0	14
Region type 1	15
Region type 2	16
Unknown color	17
Black	18
Blue	19
Red	20
Green	21
Cyan	22
Magenta	23
Yellow	24
White	25

U.S. 6/4/85 <sup>7</sup> Table B.2 lists the Ids associated with the relations used in the Belief Model.

Table B.2 <sup>7</sup>

U.S. 6/4/85

Relation Type	Id
North	1
South	2
East	3
West	4
Contains	5
Contained By	6
Adjacent To	7

## Belief Model: Rules

15 (belief-model (class1 1) (shadow1 1) (relation 6) (class2 13) (shadow2 1) (mean 0.5313) (stddev 0.4990) (prob 0.5313))  
 (belief-model (class1 2) (shadow1 1) (relation 1) (class2 1) (shadow2 1) (mean 0.5) (stddev 0.5) (prob 0.5))  
 (belief-model (class1 2) (shadow1 1) (relation 1) (class2 3) (shadow2 0) (mean 0.8333) (stddev 0.6872) (prob 0.6667))  
 (belief-model (class1 2) (shadow1 1) (relation 1) (class2 24) (shadow2 0) (mean 1.5) (stddev 1.2583) (prob 0.6667))  
 (belief-model (class1 2) (shadow1 1) (relation 3) (class2 20) (shadow2 0) (mean 1.5) (stddev 1.5) (prob 0.6667))